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Bioeconomic Modelling for Fisheries and Aquaculture.

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Abstract

Developing and parameterising fisheries bioeconomic models is seen as playing an important role in the evaluation of proposed fisheries management strategies. One of the key challenges in doing this has been the different aggregation levels of the biological and economic data. For example, economic data (costs, prices etc) is aggregated at the supra-region level as a function of fleet components, whereas biological data is collected at the smaller regional level. Management plan evaluations are required at the regional level which means methods must be developed to scale and merge the economic and biological data at this level.

Here we present a method based on the use of transversal variables (such as effort). By calculating a 'unit cost per effort' at the supraregion level, we are able to estimate costs at the regional level. This is made more difficult by the aggregation of fishing metiers and gears in the economic data, which have their own cost structure. Linear modelling techniques are used to help overcome to this issue.

This report presents these methods using the North Sea fisheries as a case study.

Note that this report was not prepared using MS Word. It was prepared using Latex / KnitR and R. This allows the computer code that was used to generate the results to be embedded in the report and executed during the report compilation, including the plotting of figures. This is preferable for scientific report writing as it ensures that the results presented here are 'live'. Consequently, the following report may not strictly adhere to the JRC template.

Adding economics to FCube
Notes

immediate

April 8, 2015

Contents

1 Introduction

This analysis is recovered from WKBEM. The idea was to compute costs per unit of effort at the metier level of the fleet as defined in DCF level 4 (aka "gear" for shortness). Mainly that's the aggregation we use for stock assessment and forecasting. So that it's possible to scale information, e.g. aggregated for MAPs analysis, and add an economic component to it.

The costs were computed at the metier level as a weighted average of the costs reported by member states at the level of the so called fleet segment. Using these data a set of mixed effects models were fit using the fleet segment as a random effect and as fixed effects member state, year (only for variable costs), gear (metier level 4) and length-over-all. Finally a set of predictions were carried out to compute the modeled value and confidence intervals (0.95).

Note that:

- variable costs = energy costs + other variable costs + repair and maintenance costs
- fixed costs = annual depreciation costs + other non variable costs + license costs
- crew costs = crew wage + unpaid labour

1.1 Data quality

In a recent meeting (Zagreb's workshop) the quality of the data was discussed and their conclusions was that each member state was processing the effort data differently. This situation has an impact on the analysis. IMO there are two issues that must be taken into account when using this dataset:

- Predictions shouldn't be crossed between member states. If one needs to fill gaps in data should do it as muh as possible using the same member state data.
- The analysis of costs time series should be made relative. Using ICES jargon, should be used only for trends.

We'll try to stick to these recommendations although is not always possible.

```
# ======================================================
# libraries and constants
# ======================================================
# rm(list=ls())
library(lattice)
library(MASS)
library(plyr)
library(dplyr)
library(reshape2)
library(lme4)
library(ggtern)
source("funs.R")

# period
yrs <- 2008:2012

# ====================================================== Read
# data ======================================================

# codes
codes.ft <- read.csv("fishingTech.csv")
codes.gr <- read.csv("gearTypes.csv")
codes.loa <- read.csv("loa.csv")
```

```
codes.ms <- read.csv("ms.csv")

# data
eff.orig <- read.csv("effort_by_gear.csv", sep = ";", stringsAsFactors = FALSE)
land.orig <- read.csv("landings_by_gear.csv", sep = ";", stringsAsFactors = FALSE)
inflation <- read.csv("ratio.csv", stringsAsFactors = FALSE)
load("ecovars.orig")
ecovars.orig$year <- as.numeric(as.character(ecovars.orig$year))
```

2 Methods

For simplicity let's call the economic aggregation of fishing operations, fleet segments, and the "biological" metier. For fleet segments the catch device is called "fishing technique", while for metiers is called "gear type". I don't like these names and I think they're adding confusion to an already complex system. For now it doesn't matter.

The analysis was carried out in 3 major steps:

1. Compute the standardized economic variables (fixed costs by vessel, variable costs by unit of effort (kwday) and crew costs by euro of revenue - aka crew share) by gear type, member state, length over all class and year. The variables were computed as a weighted average of the standardized economic variables at the fleet segment level. These maths may need revision, anyway considering one year, one supra region and one vessel length class; if v is the standardized economic variable, T is the transversal or standardizing variable (e.g. effort), i =fleet segment, j =sub region and g =gear type:
$$v_{jg} = \sum_i v_{ijg} \frac{T_{ijg}}{\sum_i T_{gj}}$$
$$v_{ijg} = \frac{E_i}{T_i}$$
2. Fit mixed effects models using fishing technique as a random effect and as fixed effects gear type, member state, length over all class and year.
3. use the models to predict the standardized economic variables by gear type, member state, year and length over all class.
4. Populate FCube fleets' fixed, variable and crewshare slots.

3 Results

3.1 Compute standardized economic variables

3.1.1 Process data

A cluster aggregates segments (e.g. if not many vessels in a segment, they get combined into a cluster).

Add cluster to the eff, land and economic data, allowing us to link datasets later on.

Not all "by" in eff, lnd and eco are in clu so we are missing some clusters, which will be built from fleet segment.

```
# ------------------------------------------------------
# clusters
# ------------------------------------------------------
# Effort
```

```
eff <- left_join(eff.orig, clu.orig[, c("country_code", "year",
    "supra_reg", "fishing_tech", "vessel_length", "cluster")],
    by = c("country_code", "year", "supra_reg", "fishing_tech",
        "vessel_length"))
df0 <- eff[is.na(eff$cluster), ]
df0 <- transform(df0, cluster = paste(supra_reg, fishing_tech,
    vessel_length, sep = ""))
eff <- rbind(eff[!is.na(eff$cluster), ], df0)
rm(df0)

# Landings
lnd <- left_join(land.orig, clu.orig[, c("country_code", "year",
    "supra_reg", "fishing_tech", "vessel_length", "cluster")],
    by = c("country_code", "year", "supra_reg", "fishing_tech",
        "vessel_length"))
df0 <- lnd[is.na(lnd$cluster), ]
df0 <- transform(df0, cluster = paste(supra_reg, fishing_tech,
    vessel_length, sep = ""))
lnd <- rbind(lnd[!is.na(lnd$cluster), ], df0)
rm(df0)

# Economics
eco <- left_join(ecovars.orig[, -1], clu.orig[, c("country_code",
    "year", "supra_reg", "fishing_tech", "vessel_length", "cluster")],
    by = c("country_code", "year", "supra_reg", "fishing_tech",
        "vessel_length"))
df0 <- eco[is.na(eco$cluster), ]
df0 <- transform(df0, cluster = paste(supra_reg, fishing_tech,
    vessel_length, sep = ""))
eco <- rbind(eco[!is.na(eco$cluster), ], df0)
rm(df0)

# -----------------------------------------------------
# subset active vessels and area 27
# -----------------------------------------------------

eco <- subset(eco, supra_reg == "AREA27" & fishing_tech != "INACTIVE" &
    year %in% yrs)
eff <- subset(eff, supra_reg == "AREA27" & fishing_tech != "INACTIVE" &
    year %in% yrs)
lnd <- subset(lnd, supra_reg == "AREA27" & fishing_tech != "INACTIVE" &
    year %in% yrs)

# -----------------------------------------------------
# Correction by inflation
# -----------------------------------------------------

# index - correct up to 2012
infIndex <- subset(inflation[, -4], year < 2013)
infIndex[infIndex$year == 2012, "inflation"] <- 0
infIndex <- infIndex[order(infIndex$year, decreasing = TRUE),
    ]
infIndex <- mutate(group_by(infIndex, country_code), inflation = cumprod(inflation/100 +
    1))

# economics
eco <- merge(eco, infIndex, by.x = c("country_code", "year"),
    by.y = c("country_code", "year"), all.x = TRUE)
```

```r
vars2fix <- c("totenercost", "totvarcost", "totdepcost", "totnovarcost",
    "OPR", "totrepcost", "totcrewwage", "totunpaidlab", "totvallandg",
    "totrightscost", "totlandginc", "totrightsinc", "totinvest",
    "tototherinc", "totrights", "totdeprep")
df0 <- subset(eco, variable %in% vars2fix)
df0 <- transform(df0, value = value * inflation)
eco <- rbind(df0, subset(eco, !(variable %in% vars2fix)))

# landings
lnd <- merge(lnd, infIndex, by.x = c("country_code", "year"),
    by.y = c("country_code", "year"), all.x = TRUE)
lnd <- transform(lnd, totvallandgFix = totvallandg * inflation)
```

3.1.2 Compute costs

Sum fixed costs, variable costs, crew wages, effort (kw and days) and capacity over (country_code, year, supra_reg, fishing_tech, vessel_length, cluster).

Note that if one of the cost components is missing (NA), costs are not computed.

```r
# -----------------------------------------------------
# compute costs
# -----------------------------------------------------

fixCosts <- c("totdepcost", "totnovarcost", "totrightscost")
varCosts <- c("totenercost", "totvarcost", "totrepcost")
crwCosts <- c("totcrewwage", "totunpaidlab")

df0 <- dcast(eco[, -9], country_code + year + supra_reg + fishing_tech +
    vessel_length + cluster ~ variable)
csts <- df0[, c("country_code", "year", "supra_reg", "fishing_tech",
    "vessel_length", "cluster")]
csts$fCst <- apply(df0[, fixCosts], 1, sum)
csts$vCst <- apply(df0[, varCosts], 1, sum)
csts$cCst <- apply(df0[, crwCosts], 1, sum)
csts$eff <- df0[, "totkwfishdays"]
csts$cap <- df0[, "totves"]
csts$emp <- df0[, "totharmfte"]

# -----------------------------------------------------
# compute landings and effort
# ----------------------------------------------------- Get
# total landings revenue, landings weight and landings price
# by country_code, year, supra_reg, fishing_tech,
# vessel_length, sub_reg, gear_type, cluster For landings we
# are summing over species.
# -----------------------------------------------------

revn <- summarise(group_by(lnd, country_code, year, supra_reg,
    fishing_tech, vessel_length, sub_reg, gear_type, cluster),
    wLnd = sum(totwghtlandg, na.rm = TRUE), rLnd = sum(totvallandgFix,
        na.rm = TRUE), pLnd = sum(totvallandgFix, na.rm = TRUE)/sum(totwghtlandg,
        na.rm = TRUE))
```

3.1.3 Compute standardized economic variables

```
# ====================================================
# Computing indicators per cluster
# ----------------------------------------------------
# Economic data has been summarised by country_code, year,
# supra_reg, fishing_tech, vessel_length, cluster Landings
# and effort data is by country_code, year, supra_reg,
# fishing_tech, vessel_length, cluster, sub_reg, gear_type
# Use cluster field to move from economic data to effort data
# ====================================================

# ----------------------------------------------------
# Variable costs
# ----------------------------------------------------

# compute standardized economic variable

# Rename for moving into eff data
csts$effEcon <- csts$eff

# Join the economic variable cost data with the effort data
# The vCst data is for the cluster, country_code, year
# combination
eff <- left_join(eff, csts[, c("cluster", "country_code", "year",
    "vCst", "effEcon")], by = c("cluster", "country_code", "year"))

# Effort data is present in the effort dataset (duh!)  Sum
# this over cluster / country / year and compare with data
# from Econ data
df0 <- summarise(group_by(eff, cluster, country_code, year),
    effEff = sum(totkwfishdays), effEcon = effEcon[1])

# Put the clustered eff data into eff
eff <- left_join(eff, df0[, c("country_code", "cluster", "year",
    "effEff")])

# Make a combined column of days effort - use Econ, fill in
# missing data with data in Eff
eff$eff <- eff$effEcon
eff[is.na(eff$eff), "eff"] <- eff[is.na(eff$eff), "effEff"]

# Make column of var cost by effort (for cluster / year /
# country) This rate is same across whole cluster (including
# subreg etc)
eff$unitVcst <- eff$vCst/eff$eff
eff$effEcon <- eff$effEff <- NULL

# ---------------------------------------------------- Crew
# costs & share & total revenue from fishing
# ----------------------------------------------------

# compute standardized economic variable

# Add the crewCosts into revn
revn <- left_join(revn, csts[, c("country_code", "year", "cluster",
    "cCst")], by = c("country_code", "year", "cluster"))

# Crew share by cluster
revn <- mutate(group_by(revn, cluster, country_code, year), cShr = cCst/sum(rLnd),
```

```
    totalCcst = cCst, totalRlnd = sum(rLnd))

# ------------------------------------------------------
# Fixed costs
# ------------------------------------------------------

# compute standardized economic variable

# Join the economic variable cost data with the effort data
# The fCst data is for the cluster, country_code, year
# combination
eff <- left_join(eff, csts[, c("cluster", "country_code", "year",
    "fCst", "cap")], by = c("cluster", "country_code", "year"))

# Make column of fix cost by effort (for cluster / year /
# country) This rate is same across whole cluster (including
# subreg etc)
eff$unitFcst <- eff$fCst/eff$cap

# ======================================================
# Computing indicators per gear type NOTE: crossing segments
# and sub regions
# ======================================================

eff <- ddply(eff, .(country_code, year, vessel_length, gear_type),
    function(x) {
        x$vCbar <- weighted.mean(x$unitVcst, x$totkwfishdays,
            na.rm = T)
        x$fCbar <- weighted.mean(x$unitFcst, x$cap, na.rm = T)
        x
    })

revn <- ddply(revn, .(country_code, year, vessel_length, gear_type),
    function(x) {
        x$cSbar <- weighted.mean(x$cShr, x$rLnd, na.rm = T)
        x
    })
```

3.2 Model standardized costs

3.2.1 Prepare datasets

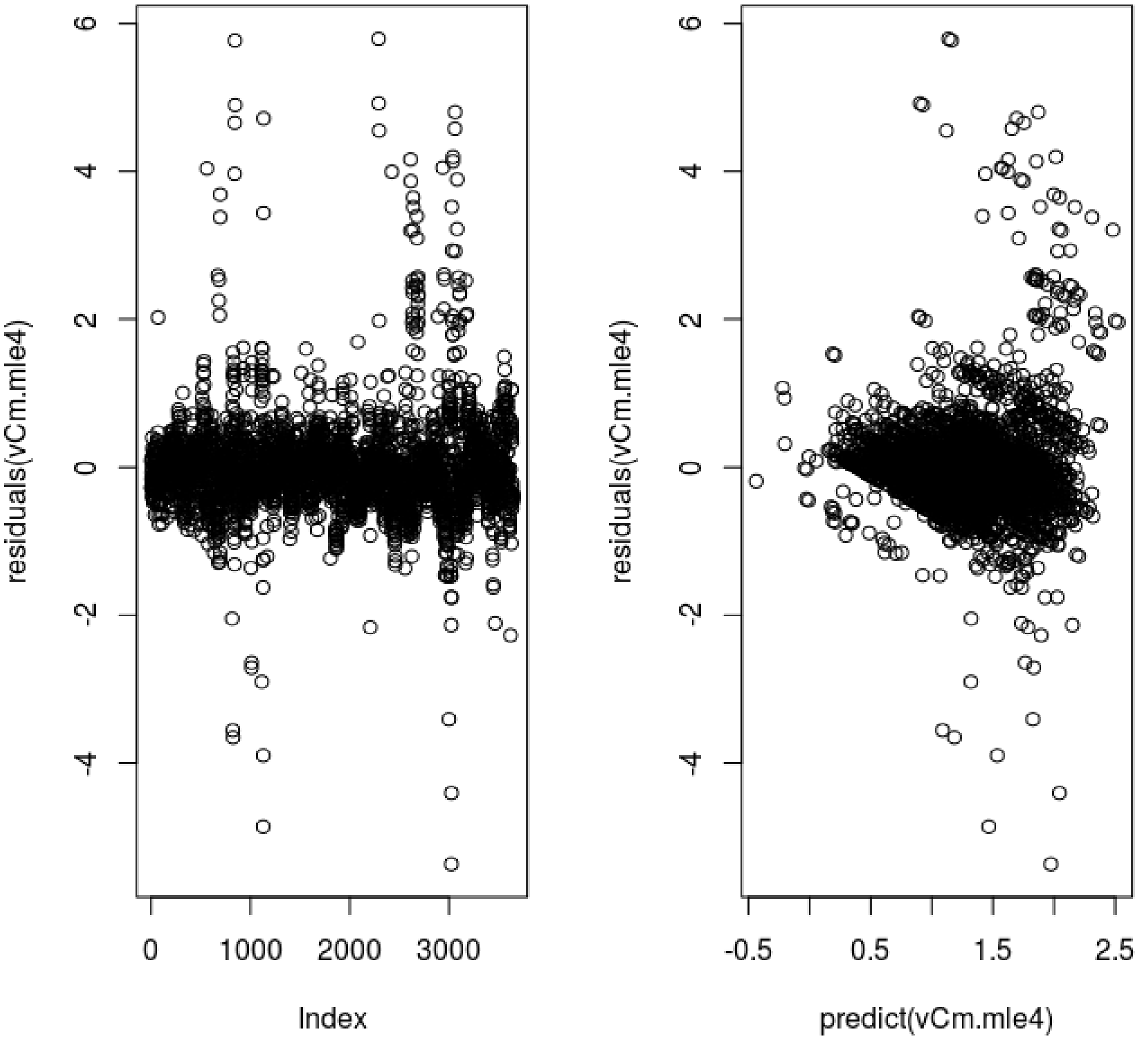
```
# for fixed and variable costs
Cm.df <- as.data.frame(summarise(group_by(eff, cluster, country_code,
    year, vessel_length, fishing_tech, gear_type), eff = eff[1],
    cap = cap[1], vCbar = vCbar[1], fCbar = fCbar[1]))
names(Cm.df) <- c("clt", "ms", "y", "loa", "ft", "gr", "eff",
    "cap", "vCbar", "fCbar")
# remove gears with less than 10 observations, NO and NK
df0 <- table(Cm.df$gr)
v0 <- names(df0)[df0 > 10]
v0 <- v0[!(v0 %in% c("NO", "NK"))]
Cm.df <- subset(Cm.df, gr %in% v0)

# for variable costs(levels set mannualy to meet all
# datasets)
```

```
vCm.df <- subset(Cm.df, vCbar > 0 & !is.na(eff))
vCm.df <- transform(vCm.df, y = as.factor(y), loa = as.factor(loa),
    ms = as.factor(ms), gr = as.factor(gr))
vCm.df <- transform(vCm.df, y = relevel(y, "2012"), loa = relevel(loa,
    "VL1218"), ms = relevel(ms, "GBR"), gr = relevel(gr, "OTB"))

# for fixed costs
fCm.df <- subset(Cm.df, fCbar > 0 & !is.na(cap))
fCm.df <- transform(fCm.df, y = as.factor(y), loa = as.factor(loa),
    ms = as.factor(ms), gr = as.factor(gr))
fCm.df <- transform(fCm.df, y = relevel(y, "2012"), loa = relevel(loa,
    "VL1218"), ms = relevel(ms, "GBR"), gr = relevel(gr, "OTB"))

# for crew share
cSm.df <- as.data.frame(summarise(group_by(revn, cluster, country_code,
    year, vessel_length, fishing_tech, gear_type), twLnd = sum(wLnd,
    na.rm = T), trLnd = totalRlnd[1], tccLnd = totalCcst[1],
    cSbar = cSbar[1]))
names(cSm.df) <- c("clt", "ms", "y", "loa", "ft", "gr", "twLnd",
    "trLnd", "tcCst", "cSbar")
cSm.df <- subset(cSm.df, cSbar < 1 & cSbar > 0 & gr %in% v0)
cSm.df <- subset(cSm.df, !is.na(trLnd))
cSm.df <- transform(cSm.df, y = as.factor(y), loa = as.factor(loa),
    ms = as.factor(ms), gr = as.factor(gr))
cSm.df <- transform(cSm.df, y = relevel(y, "2012"), loa = relevel(loa,
    "VL1218"), ms = relevel(ms, "GBR"), gr = relevel(gr, "OTB"))

# for predictions
nd0 <- as.data.frame(summarise(group_by(eff, country_code, year,
    vessel_length, gear_type), vCbar = vCbar[1], fCbar = fCbar[1],
    idx = paste(country_code, year, vessel_length, gear_type,
        sep = ":")))
names(nd0) <- c("ms", "y", "loa", "gr", "vCbar", "fCbar", "idx")

nd1 <- as.data.frame(summarise(group_by(revn, country_code, year,
    vessel_length, gear_type), rLnd = sum(rLnd, na.rm = T), cSbar = cSbar[1],
    idx = paste(country_code, year, vessel_length, gear_type,
        sep = ":")))
names(nd1) <- c("ms", "y", "loa", "gr", "rLnd", "cSbar", "idx")

nd <- merge(nd0, nd1[, c("rLnd", "cSbar", "idx")], all = TRUE)

# remove gears with less than 10 observations, NO and NK
nd <- subset(nd, gr %in% v0)
nd <- transform(nd, y = as.factor(y), loa = as.factor(loa), ms = as.factor(ms),
    gr = as.factor(gr))
nd <- transform(nd, y = relevel(y, "2012"), loa = relevel(loa,
    "VL1218"), ms = relevel(ms, "GBR"), gr = relevel(gr, "OTB"))
rm(nd0, nd1)
```

3.2.2 Fit lme models

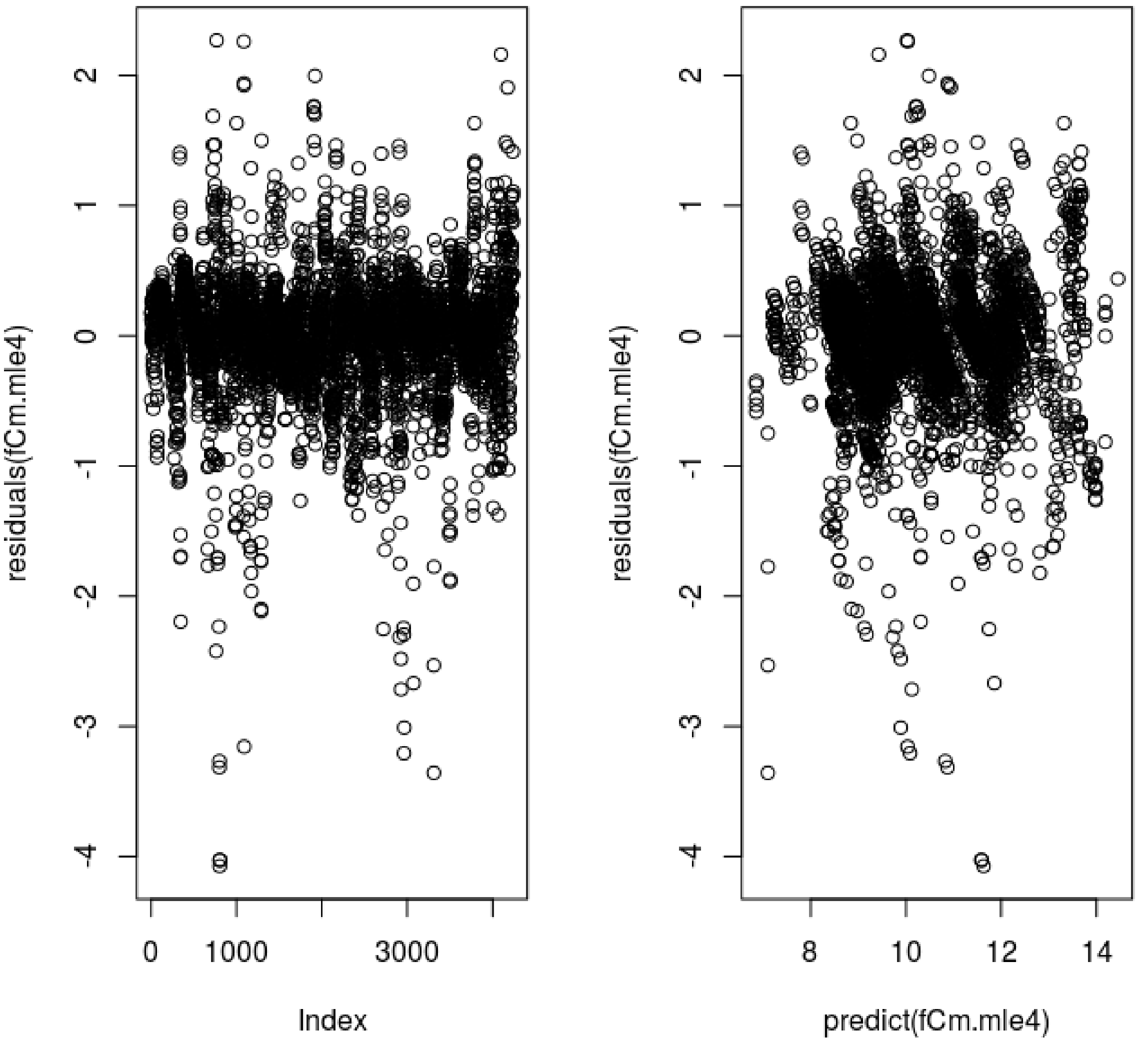
```
# ------------------------------------------------------- Fit
# lme model with log transform to variable costs
# ------------------------------------------------------- fit
# model
```

```
vCm.mle4 <- lmer(log(vCbar) ~ ms + gr + loa + y + (1 | ft), data = vCm.df)

par(mfrow = c(1, 2))
plot(residuals(vCm.mle4))
plot(residuals(vCm.mle4) ~ predict(vCm.mle4))
```



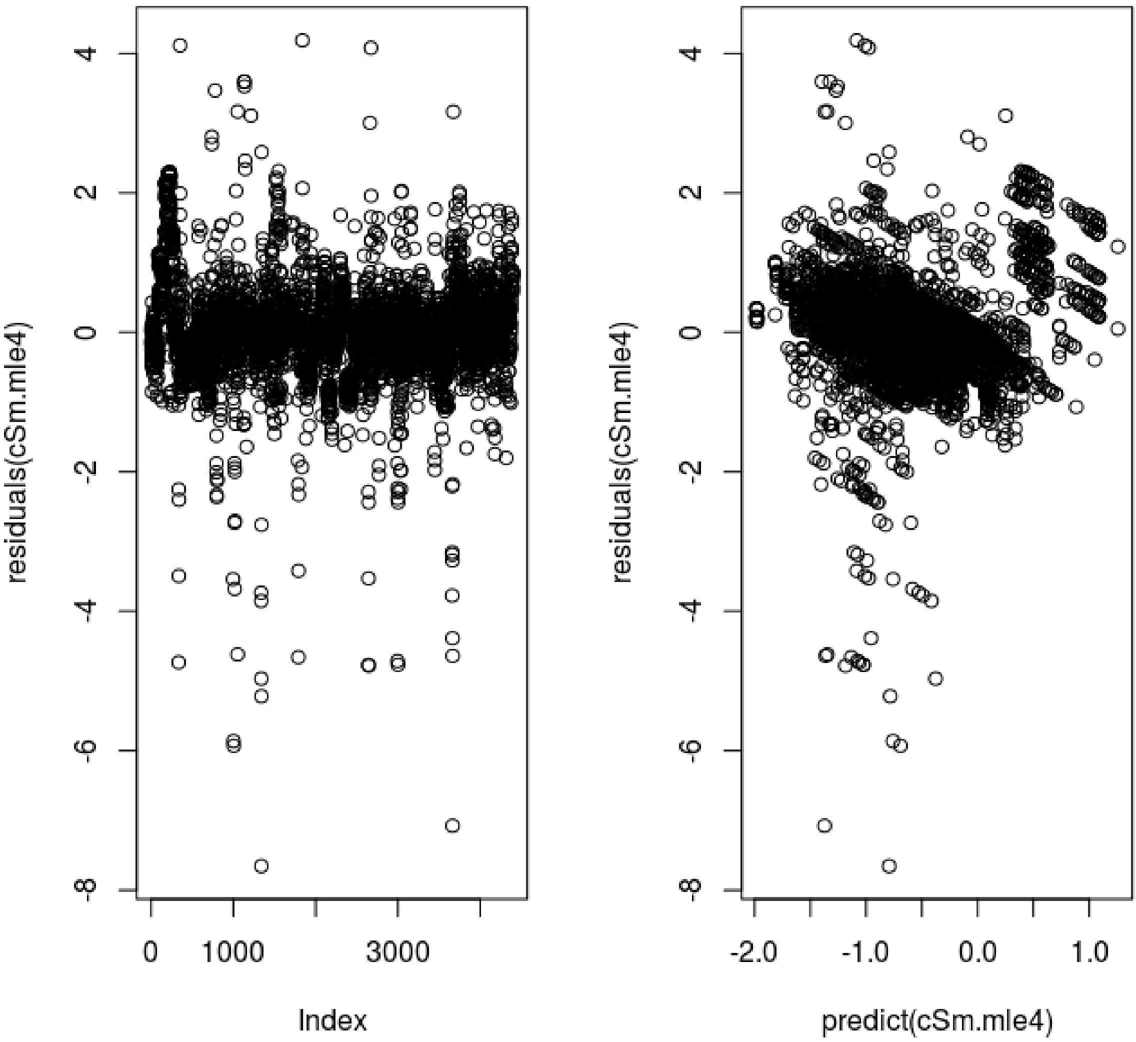

```
# bootstrap
vCm.bs <- bootMer(vCm.mle4, FUN = function(x) predict(x, re.form = ~0,
    type = "response", newdata = nd), 250)

# predict
nd$vCbarPred <- apply(exp(vCm.bs$t), 2, mean)
nd$vCbarVar <- apply(exp(vCm.bs$t), 2, var)
nd$vCbarupp <- apply(exp(vCm.bs$t), 2, quantile, prob = 0.975,
    na.rm = TRUE)
nd$vCbarlow <- apply(exp(vCm.bs$t), 2, quantile, prob = 0.025,
    na.rm = TRUE)

# ----------------------------------------------------- fit
```

```r
# lme model with log transform to fixed costs
# ------------------------------------------------------

# fit model
fCm.mle4 <- lmer(log(fCbar) ~ ms + gr + loa + (1 | ft), data = fCm.df)

par(mfrow = c(1, 2))
plot(residuals(fCm.mle4))
plot(residuals(fCm.mle4) ~ predict(fCm.mle4))
```




```r
# bootstrap
fCm.bs <- bootMer(fCm.mle4, FUN = function(x) predict(x, re.form = ~0,
    type = "response", newdata = nd), 250)

# predict
nd$fCbarPred <- apply(exp(fCm.bs$t), 2, mean)
nd$fCbarVar <- apply(exp(fCm.bs$t), 2, var)
nd$fCbarUpp <- apply(exp(fCm.bs$t), 2, quantile, prob = 0.975,
    na.rm = TRUE)
```

```
nd$fCbarLow <- apply(exp(fCm.bs$t), 2, quantile, prob = 0.025,
    na.rm = TRUE)

# ------------------------------------------------------ fit
# lme model with logit transform to crew share
# ------------------------------------------------------

# fit model
cSm.mle4 <- lmer(logit(cSbar) ~ ms + gr + loa + (1 | ft), data = cSm.df)

par(mfrow = c(1, 2))
plot(residuals(cSm.mle4))
plot(residuals(cSm.mle4) ~ predict(cSm.mle4))
```




```
# bootstrap
cSm.bs <- bootMer(cSm.mle4, FUN = function(x) predict(x, re.form = ~0,
    type = "response", newdata = nd), 250)

# predict
```

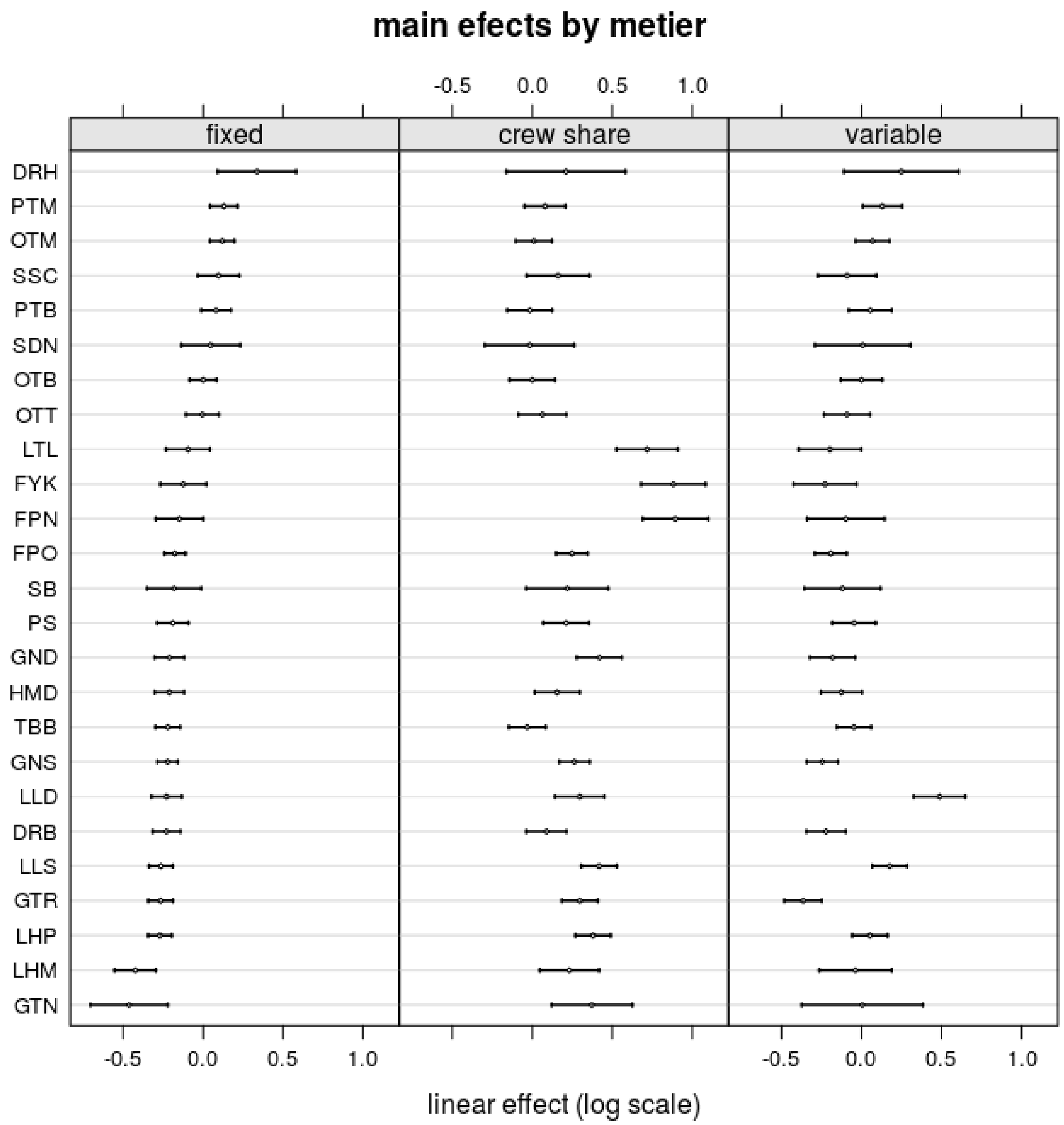
```r
nd$cSbarPred <- apply(inv.logit(cSm.bs$t), 2, mean)
nd$cSbarVar <- apply(inv.logit(cSm.bs$t), 2, var)
nd$cSbarUpp <- apply(inv.logit(cSm.bs$t), 2, quantile, prob = 0.975,
    na.rm = TRUE)
nd$cSbarLow <- apply(inv.logit(cSm.bs$t), 2, quantile, prob = 0.025,
    na.rm = TRUE)
```

3.2.3 Factors affecting the costs - fixed effects coefficients

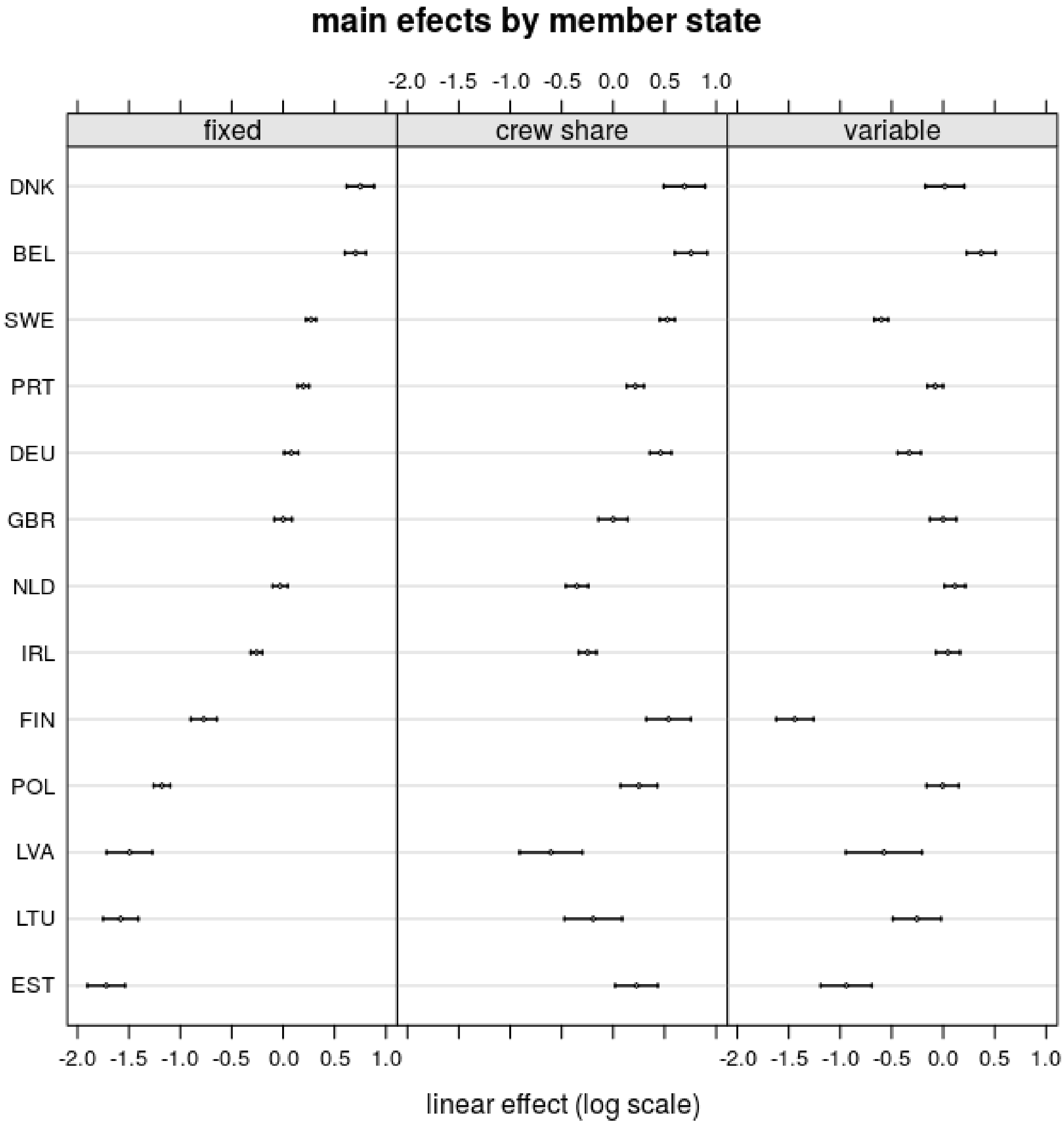
```r
fixef.res <- getFixEffRes(fCm.mle4, fCm.df, "fixed")
fixef.res <- rbind(fixef.res, getFixEffRes(vCm.mle4, vCm.df,
    "variable"))
fixef.res <- rbind(fixef.res, getFixEffRes(cSm.mle4, cSm.df,
    "crew share"))
fixef.res <- merge(fixef.res, codes.gr, by.x = "level", by.y = "code",
    all.x = T)
```

```r
pset <- list(strip.background = list(col = "gray90"))
pfun <- function(x, y, ...) {
    panel.abline(h = y, col = "gray90", wd = 0.5)
    ll <- length(x)
    x0 <- x[1:(ll/3)]
    y0 <- y[1:(ll/3)]
    x1 <- x[(ll/3 + 1):(2 * ll/3)]
    y1 <- y[(ll/3 + 1):(2 * ll/3)]
    # panel.segments(x0,y0,x1,y1, lwd=1.5)
    panel.arrows(x0, y0, x1, y1, lwd = 1.5, code = 3, angle = 90,
        length = 0.01)
    x <- x[(2 * ll/3 + 1):(ll)]
    y <- y[(2 * ll/3 + 1):(ll)]
    panel.points(x, y, pch = 23, cex = 0.3, col = 1, fill = "white")
}
```

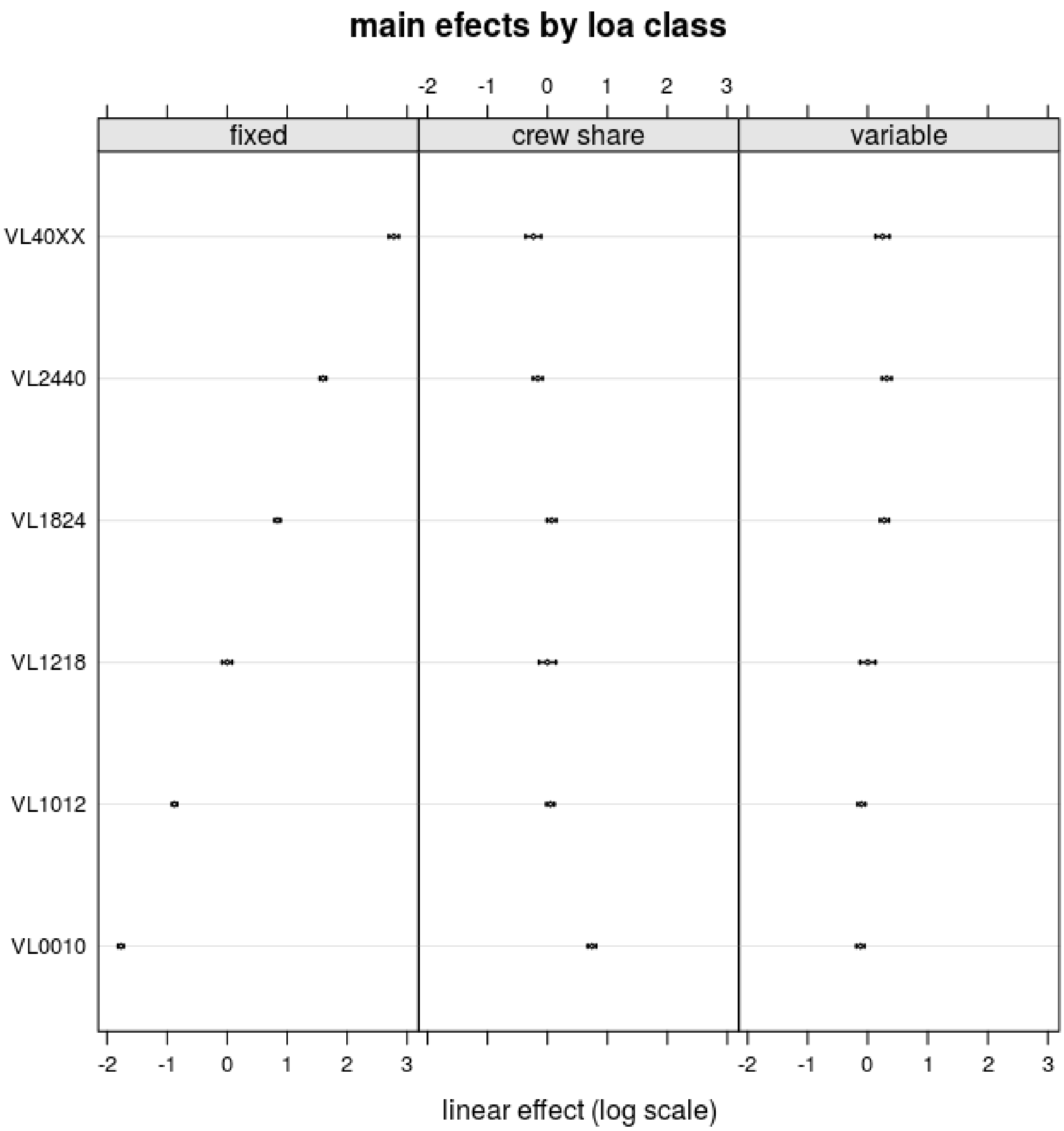
```r
df0 <- subset(fixef.res, eff == "gr")
df0$cst <- relevel(factor(df0$cst), "fixed")

df1 <- subset(df0, cst == "fixed")[, c("level", "est")]
names(df1) <- c("level", "sort")
df0 <- merge(df0, df1)

dotplot(reorder(level, sort) ~ low + upp + est | cst, data = df0,
    panel = pfun, par.settings = pset, layout = c(3, 1), xlab = "linear effect (log scale)",
    main = "main efects by metier")
```




```
df0 <- subset(fixef.res, eff == "ms")
df0$cst <- relevel(factor(df0$cst), "fixed")

df1 <- subset(df0, cst == "fixed")[, c("level", "est")]
names(df1) <- c("level", "sort")
df0 <- merge(df0, df1)

dotplot(reorder(level, sort) ~ low + upp + est | cst, data = df0,
    panel = pfun, par.settings = pset, layout = c(3, 1), xlab = "linear effect (log scale)",
    main = "main efects by member state")
```




```
df0 <- subset(fixef.res, eff == "loa")
df0$cst <- relevel(factor(df0$cst), "fixed")

df1 <- subset(df0, cst == "fixed")[, c("level", "est")]
names(df1) <- c("level", "sort")
df0 <- merge(df0, df1)

dotplot(reorder(level, sort) ~ low + upp + est | cst, data = df0,
    panel = pfun, par.settings = pset, layout = c(3, 1), xlab = "linear effect (log scale)",
    main = "main efects by loa class")
```



4 Adding economics to the FCube fleets

To add economics to FCube it was necessary to map FCube fleets into the standardized dataset fleets. This was done with the table below.

```
library(FLFleet)
load("../fleets/03_NS Making FLFleets_withoutWoS v2_R215_KW.RData")
f3flt <- read.csv("f3flts.csv")
kable(f3flt)
```

f3flt	ms	gr	loa
BE_Beam>=24	BEL	TBB	VL2440
BE_Otter	BEL	OTB	NA
DK_FDF	DNK	NA	NA
DK_Otter<24	DNK	OTB	VL1218
DK_Otter<24	DNK	OTB	VL1824
DK_Otter24-40	DNK	OTB	VL2440
DK_Seine	DNK	NA	NA
DK_Static	DNK	GTN	NA
EN_Beam	GBR	TBB	NA
EN_FDF	GBR	NA	NA
EN_Otter<24	GBR	OTB	VL1218
EN_Otter<24	GBR	OTB	VL1824
EN_Otter>=40	GBR	OTB	VL40XX
EN_Otter24-40	GBR	OTB	VL2440
EN_U10	GBR	NA	VL0010
FR_Beam	NA	TBB	NA
FR_Nets	NA	GTN	NA
FR_Otter>=40	NA	OTB	VL40XX
FR_Otter10-40	NA	OTB	VL1218
FR_Otter10-40	NA	OTB	VL1824
FR_Otter10-40	NA	OTB	VL2440
FR_Otter10-40	NA	OTB	VL1012
FR_U10m	NA	NA	VL0010
GE_Beam>=24	DEU	TBB	VL2440
GE_FDF	DEU	NA	NA
GE_Otter<24	DEU	OTB	VL1218
GE_Otter<24	DEU	OTB	VL1824
GE_Otter>=40	DEU	OTB	VL40XX
GE_Otter24-40	DEU	OTB	VL2440
NL_Beam<24	NLD	TBB	VL1218
NL_Beam<24	NLD	TBB	VL1824
NL_Beam>=40	NLD	TBB	VL40XX
NL_Beam24-40	NLD	TBB	VL2440
NL_Otter	NLD	OTB	NA
NO_Otter<40	NA	OTB	NA
NO_Otter>=40	NA	OTB	VL40XX
NO_Static	NA	GTN	NA
SC_FDF	GBR	NA	NA
SC_Otter<24	GBR	OTB	VL1218
SC_Otter<24	GBR	OTB	VL1824
SC_Otter>=24	GBR	OTB	VL40XX
SC_Otter>=24	GBR	OTB	VL2440
SC_Static	GBR	NA	NA
SC_U10_OTB	GBR	OTB	VL0010
SW_Otter	SWE	OTB	NA
OTH_OTH	NA	NA	NA

Using the mapping the average value for each economic variable was computed for each FCube fleet. The code is not the most elegant ...

```
# merge complete cases
df0 <- merge(nd, f3flt)

lst <- lapply(split(df0, as.character(df0$f3flt)), function(x) {
    df0 <- t(as.data.frame(apply(x[, c("vCbarPred", "fCbarPred",
        "cSbarPred")], 2, mean, na.rm = T)))
    rownames(df0) <- x$f3flt[1]
```

```
    df0
})

f3flt.eco <- do.call("rbind", lst)

# cases with no loa

df0 <- f3flt[!(f3flt$f3flt %in% rownames(f3flt.eco)) & is.na(f3flt$loa),
    ]
df0 <- merge(nd, df0, by.x = c("ms", "gr"), by.y = c("ms", "gr"))

lst <- lapply(split(df0, as.character(df0$f3flt)), function(x) {
    df0 <- t(as.data.frame(apply(x[, c("vCbarPred", "fCbarPred",
        "cSbarPred")], 2, mean, na.rm = T)))
    rownames(df0) <- x$f3flt[1]
    df0
})

f3flt.eco <- rbind(f3flt.eco, do.call("rbind", lst))

# cases with no gr

df0 <- f3flt[!(f3flt$f3flt %in% rownames(f3flt.eco)) & is.na(f3flt$gr),
    ]
df0 <- merge(nd, df0, by.x = c("ms", "loa"), by.y = c("ms", "loa"))

lst <- lapply(split(df0, as.character(df0$f3flt)), function(x) {
    df0 <- t(as.data.frame(apply(x[, c("vCbarPred", "fCbarPred",
        "cSbarPred")], 2, mean, na.rm = T)))
    rownames(df0) <- x$f3flt[1]
    df0
})

f3flt.eco <- rbind(f3flt.eco, do.call("rbind", lst))

# cases with no gr and no loa

df0 <- f3flt[!(f3flt$f3flt %in% rownames(f3flt.eco)) & is.na(f3flt$gr) &
    is.na(f3flt$loa), ]
df0 <- merge(nd, df0, by.x = c("ms"), by.y = c("ms"))

lst <- lapply(split(df0, as.character(df0$f3flt)), function(x) {
    df0 <- t(as.data.frame(apply(x[, c("vCbarPred", "fCbarPred",
        "cSbarPred")], 2, mean, na.rm = T)))
    rownames(df0) <- x$f3flt[1]
    df0
})

f3flt.eco <- rbind(f3flt.eco, do.call("rbind", lst))

# cases with no ms

df0 <- f3flt[!(f3flt$f3flt %in% rownames(f3flt.eco)) & is.na(f3flt$ms),
    ]
df0 <- merge(nd, df0, by.x = c("gr", "loa"), by.y = c("gr", "loa"))

lst <- lapply(split(df0, as.character(df0$f3flt)), function(x) {
    df0 <- t(as.data.frame(apply(x[, c("vCbarPred", "fCbarPred",
```

```
        "cSbarPred")], 2, mean, na.rm = T)))
    rownames(df0) <- x$f3flt[1]
    df0
})

f3flt.eco <- rbind(f3flt.eco, do.call("rbind", lst))

# cases with no ms and no loa

df0 <- f3flt[!(f3flt$f3flt %in% rownames(f3flt.eco)) & is.na(f3flt$ms) &
    is.na(f3flt$loa), ]
df0 <- merge(nd, df0, by.x = c("gr"), by.y = c("gr"))

lst <- lapply(split(df0, as.character(df0$f3flt)), function(x) {
    df0 <- t(as.data.frame(apply(x[, c("vCbarPred", "fCbarPred",
        "cSbarPred")], 2, mean, na.rm = T)))
    rownames(df0) <- x$f3flt[1]
    df0
})

f3flt.eco <- rbind(f3flt.eco, do.call("rbind", lst))

# cases with no ms and no gr

df0 <- f3flt[!(f3flt$f3flt %in% rownames(f3flt.eco)) & is.na(f3flt$ms) &
    is.na(f3flt$gr), ]
df0 <- merge(nd, df0, by.x = c("loa"), by.y = c("loa"))

lst <- lapply(split(df0, as.character(df0$f3flt)), function(x) {
    df0 <- t(as.data.frame(apply(x[, c("vCbarPred", "fCbarPred",
        "cSbarPred")], 2, mean, na.rm = T)))
    rownames(df0) <- x$f3flt[1]
    df0
})

f3flt.eco <- rbind(f3flt.eco, do.call("rbind", lst))

# cases with nothing (OTH_OTH)
df0 <- t(as.data.frame(apply(nd[, c("vCbarPred", "fCbarPred",
    "cSbarPred")], 2, mean, na.rm = T)))
rownames(df0) <- f3flt[!(f3flt$f3flt %in% rownames(f3flt.eco)),
    "f3flt"]
f3flt.eco <- rbind(f3flt.eco, df0)
```

And finally added to the relevant FCube fleet.

```
# populating the FLFleet objects

fleets <- lapply(fleets, function(x, eco = f3flt.eco) {
    fcost(x) <- capacity(x) * eco[rownames(eco) == name(x), "fCbarPred"]
    fcost(x)[fcost(x) <= 0] <- NA
    effort(x)[effort(x) <= 0] <- NA
    crewshare(x) <- eco[rownames(eco) == name(x), "cSbarPred"]
    for (i in names(x@metiers)) {
        vcost(metiers(x)[[i]]) <- effshare(metiers(x)[[i]]) *
            effort(x) * eco[rownames(eco) == name(x), "vCbarPred"]
    }
    x
```

```r
})

save(fleets, file = "../fleets/03_NS Making FLFleets_withoutWoS v3_R311_KWECON.RData")
```

5 Dataset with predictions

The final dataset variables definition is below:

- "idx" - row index
- "ms" - member state
- "y" - year
- "loa" - vessel length-over-all
- "gr" - gear, level 4 of DCF
- "eff" - effort in days at sea
- "vCbar" - variable costs by unit of effort
- "fCbar" - fixed costs by unit of effort
- "eCbar" - energy costs by unit of effort
- "tCbar" - total costs by unit of effort
- "rLnd" - revenue from landings
- "cSbar" - crew share (crew costs over revenue from landings)
- "vCbarPred" - variable costs by unit of effort (model prediction)
- "vCbarVar" - variable costs by unit of effort (model prediction variance)
- "vCbarupp" - variable costs by unit of effort (model prediction 0.975 quantile, upper confidence interval)
- "vCbarlow" - variable costs by unit of effort (model prediction 0.025 quantile, lower confidence interval)
- "fCbarPred" - fixed costs by unit of effort (model prediction)
- "fCbarVar" - fixed costs by unit of effort (model prediction variance)
- "fCbarupp" - fixed costs by unit of effort (model prediction 0.975 quantile, upper confidence interval)
- "fCbarlow" - fixed costs by unit of effort (model prediction 0.025 quantile, lower confidence interval)
- "cSbarPred" - crew share (model prediction)
- "cSbarVar" - crew share (model prediction variance)
- "cSbarupp" - crew share (model prediction 0.975 quantile, upper confidence interval)
- "cSbarlow" - crew share (model prediction 0.025 quantile, lower confidence interval)
- "eCbarPred" - energy costs by unit of effort (model prediction)
- "eCbarVar" - energy costs by unit of effort (model prediction variance)
- "eCbarupp" - energy costs by unit of effort (model prediction 0.975 quantile, upper confidence interval)

- "eCbarlow" - energy costs by unit of effort (model prediction 0.025 quantile, lower confidence interval)
- "tCbarPred" - total costs by unit of effort (model prediction)
- "tCbarVar" - total costs by unit of effort (model prediction variance)
- "tCbarupp" - total costs by unit of effort (model prediction 0.975 quantile, upper confidence interval)
- "tCbarlow" - total costs by unit of effort (model prediction 0.025 quantile, lower confidence interval)

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